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Applying survival analysis for assessment of forests sustainable development

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ABSTRACT

Tree mortality has traditionally been evaluated in forest inventories through summaries of dead trees by location, species, and several causal agents. Although these methods were most commonly used, in order to assess forests sustainable development, they have had limited use in detecting mortality trends and development dynamics. This study proposes the application of survival analysis for the purpose of analyzing tree mortality. Individual tree growth increments were used to estimate survival and hazard functions for the Elatia forest (Drama, Northeast Greece). These estimates provided indications of regional mortality by diameter at breast height (DBH) and diameter growth (ΔDBH) between successive measurements. Comparisons of survival/hazard curves and tests of effects of species and crown class (CC) on individual survival curves were conducted. Survival analysis technique, by using the variables of DBH and ΔDBH, could help foresters to evaluate regional tree mortality trends, and, consequently, forests sustainable development.

Contents

1. Introduction

Tree mortality in forest inventories has traditionally been evaluated using relatively simple summary statistics. Mortality information available to foresters has typically included losses in timber volume due to mortality, summaries of mortality causal agents, spatial locations of mortality, and mortality trends by species [38]. Currently, most forest management reports, in order to assess sustainable development, use this mortality evaluation methodology [1,2]. More in-depth mortality analysis has historically only been facilitated through development of individual tree mortality logistic mdels, a technique that has had limited use in national inventories [3,4] and may be inadequate for broadly defining forest development dynamics [5]. Although remotely sensed information and geographic information systems have greatly aided analysis of forest mortality, the basic analytical methodologies of forest mortality evaluation have only slowly evolved [6].

The forest sciences have historically focused on developing individual tree mortality sub-models for incorporation into growth and yield models [7–11]. Although other sciences that monitor populations of living organisms, such as the veterinary and medical sciences, have developed methodologies to evaluate mortality beyond that of the individual, the forest sciences have relatively few methodologies for evaluating tree population mortality and sustainable development assessment [6]. Commonly used forest mortality analytical techniques lack methodology for incorporating the time-dependent nature of tree mortality, hypothesis testing, censoring of observations, and tests for effects of covariates. Given the diseases and epidemics that have greatly altered forest ecosystems and future forest health issues that may occur, techniques for evaluating tree mortality and forest decline would benefit forest scientists and managers alike.

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Analytical methods developed by the medical sciences, collectively termed survival analysis, may provide the basis for development of new forest mortality analytical techniques [12,13]. Survival analysis is most often defined as a class of statistical methods for studying the occurrence and timing of events, most often death [14,15,40]. Survival analysis is unique in that it allows for censoring of observations (lack of exact time of death) and inclusion of time-dependent covariates, in addition to dealing with non-normal distributions [36,40]. Waters [16] first proposed using survival analysis to address forest mortality issues, but such applications have been restricted mainly to forest inventories in even-aged forest plantations [17–20], forest research plots [21–23] and stand table projections [24]. Although there has been significant work on the development of estimation procedures for survival and hazard functions in forest research plots [23,19] and in relation to diameter growth [25,26], survival analysis techniques have not been widely applied to forest inventory analyses due to the inherent lack of detailed time and age information for forest inventories [27]. Given the current lack of baseline forest inventory mortality analyses techniques [28] and the potential that survival analysis offers [12,6,13], an examination of survival analysis in the context of a forest inventory is warranted and may refine analysis of tree mortality and forests sustainable development.

The primary goal of this study is to estimate and interpret the central functions of survival analysis (Kaplan–Meier survival and hazard functions), on a time scale defined by growth in diameter at breast height, for Elatia forest (Drama, Northeast Greece). Specifically, the objectives of this study are:

1. to use diameter at breast height (DBH) and growth in diameter at breast height (ΔDBH) in applying survival analyses techniques;
2. to determine if Kaplan–Meier survival/hazard functions can represent actual mortality trends in a manner practical for ecological interpretation;
3. to determine species and social status effects to mortality trends.

2. Materials and methods

2.1. Data

The data for this study came from two successive measurements at Elatia forest (Drama, Northeast Greece), in the context of students practice (Dimokritos University, Greece, Department of Forestry and Management of the Environment and Natural Resources). Sample trees were surveyed in 2005 and re-measured in 2009 (Table 1). Individual trees (observations) were included that met the following criteria: alive at time one (2005) and either dead or alive at time two (2009), and DBH >12 cm at time one. Individual tree attributes measured at time one that were included as predictors of mortality in this study were diameter at breast height (DBH, cm) and crown class (CC). If a tree was dead at time two then its DBH was set equal to the DBH at time two or the DBH at time one, whichever was larger. Since a tree's DBH may shrink following death, an estimate of the maximum DBH the tree attained before death would better benefit survival analysis than an estimate of a decaying bole diameter. CC is a measure of a tree's dominance in relation to adjacent trees in the same stand and is coded as follows: 1, open grown; 2, dominant; 3, codominant; 4, intermediate; 5, suppressed. ΔDBH was calculated as the difference in DBH between time one and time two. For trees that died during the re-measurement interval (censored), ΔDBH represents less of an average growth rate.

Table 1
Mortality of sample trees at Elatia, 2005–2009.

Species	Number of measured trees	Number of trees that died
Picea abies	142	18
Fagus sylvatica	1	0
Pinus sylvestris	11	3

2.2. Survival analysis

Kaplan–Meier survival and hazard functions, are used to quantify the probability distribution of mortality in a population [29]. The survival function is defined as [14,15,36]:

$$S(t) = P(T > t) \quad (1)$$

where $S(t)$ is the probability that a death occurs at some time T at least as great as time t, but is not constrained except for being greater than 0.

The hazard function is an instantaneous mortality rate and hence is a conditional probability defined as [15,36]:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \le T \le t + \Delta t | T \ge t)}{\Delta t} \quad (2)$$

where $h(t)$ is the probability that death occurs exactly at time t, given that it has not occurred before then.

The survival function may be estimated non-parametrically by using the life-table method given by [15]:

$$\hat{S}(t_i) = \prod_{j=1}^{i-1} (1 - h_j) \quad (3)$$

where for interval i, t_i is the start of time and h_i is the conditional probability of death. For $i = 1$ and hence $t_i = 0$, the survival probability is set to 1.0.

The life-table non-parametric estimate of the hazard function at the midpoint of each time interval is given by [15]:

$$h(t_{im}) = \frac{d_i}{b_i(n_i - (w_i/2) - (d_i/2))} \quad (4)$$

where for the ith interval, t_{im} is the midpoint, d_i the number of deaths, b_i the width of the interval, n_i the number of individuals at the beginning of the interval, and w_i is the number of cases censored (exact time of death cannot be ascertained) within the interval. Note that, the survival and hazard functions are mathematical functions of each other; given one, we can compute the other.

The null hypothesis, that the survival functions are the same for two groups of individuals, may be tested by the non-parametric logrank test statistic given by [30]:

$$U_L = \sum_{j=1}^{r} (d_{1j} - e_{1j}) \quad (5)$$

where U_L is the summation over all unique event times (in both groups) and there are a total of r such times, d_{1j} is the number of deaths that occur in group 1 at time j and e_{1j} is the expected number of events in group 1 at time j. The expected number of events is given by $n_{1j}d_j/n_j$, where n_j is the total number of cases that are at risk just prior to time j, n_{1j} the number at risk just prior to time j in group 1, and d_j is the total number of deaths at time j in both groups. Squaring and dividing U_L by the estimated variance provides a χ^2 statistic. Additionally, logrank tests may be generalized to test whether covariates are associated with survival times.

As evidenced in survival analysis formulations, time to an event is the defining component of survival methods. Hence, the major

obstacle cited as limiting the application of survival analysis to forest inventories is the lack of specific tree ages and the censoring of tree mortality [27]. However, knowledge of age is not necessary for implementation of survival analyses. Any measurement unit that indicates changes in an individual's status between re-measurements may replace the traditional survival analysis variables of age and time. For forest inventories that re-measure trees at regular intervals, e.g., national inventories [31,4], DBH and ΔDBH may assign individual trees within a population to classes defined by tree size and growth. Whereas medical studies may determine survival functions for demographic cohorts across calendar years, forest inventory survival functions may be determined for DBH classes across growth [12].

In this study, time starts at the first forest inventory, when a subject begins to be at risk for the event or begins to be monitored for the event. Stating this in terms of DBH, time is ΔDBH (the increase in DBH from initial survey). Other studies [25,26] have found some success in using predicted ΔDBH to refine estimates of time of tree death. Survival function in this study $S(\Delta DBH)$ gives the probability that a tree will continue to live until its diameter has increased by at least ΔDBH. Hence, for all previously stated formulations of the non-parametric survival and hazard function estimators and logrank tests, we substituted ΔDBH for time.

Several software packages produce estimates of the survival and hazard functions. In this study, the SPSS SURVIVAL [30] was used. Trees were grouped by initial DBH into 10-cm diameter classes. The survival and hazard functions (Eqs. (1) and (2)) were compared for their forest science applicability. In addition, the survival function was further examined in terms of effects of covariates (DBH class and CC), using logrank tests (Eq. (5)).

3. Results

The survival and hazard functions were estimated separately for the three initial DBH classes for the three species in the 2005–2009 period (Figs. 1 and 2). We could say that trees of the middle diameter class ((22,32) cm) seem to have the highest survival probability (Fig. 1). For all three initial diameter classes, the hazard of death increases while ΔDBH increases. We could say that the smallest trees with the most diameter growth had the greatest mortality hazard (Fig. 2).

Hazard functions for the [12,22] cm DBH class, which appears to have the greatest mortality, were stratified by species group, in order to evaluate specific mortality trends. Risk of mortality was distinctly different between two species groups (*Picea abies* and *Pinus sylvestris*), across the biggest values of ΔDBH (Fig. 3).

Logrank tests (Table 2), which were conducted for effects of covariates on survival functions (DBH class and CC) did not show any significant effect ($p > 0.05$).

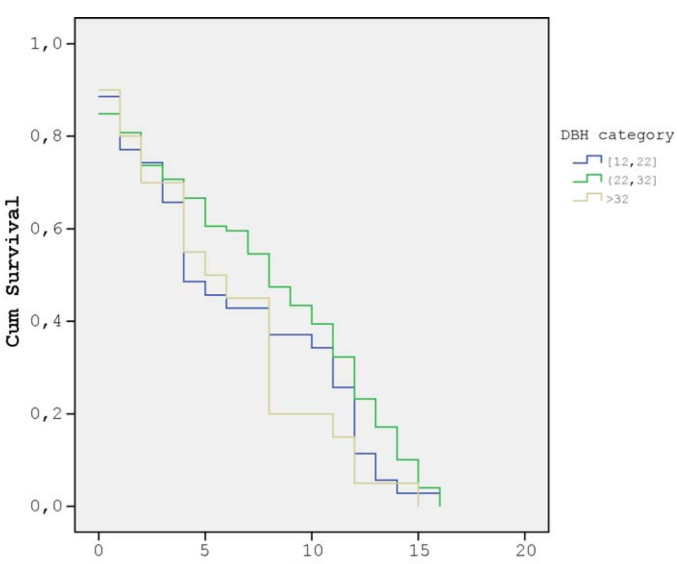


Fig. 1. Kaplan–Meier survival functions for time one diameter classes by ΔDBH.

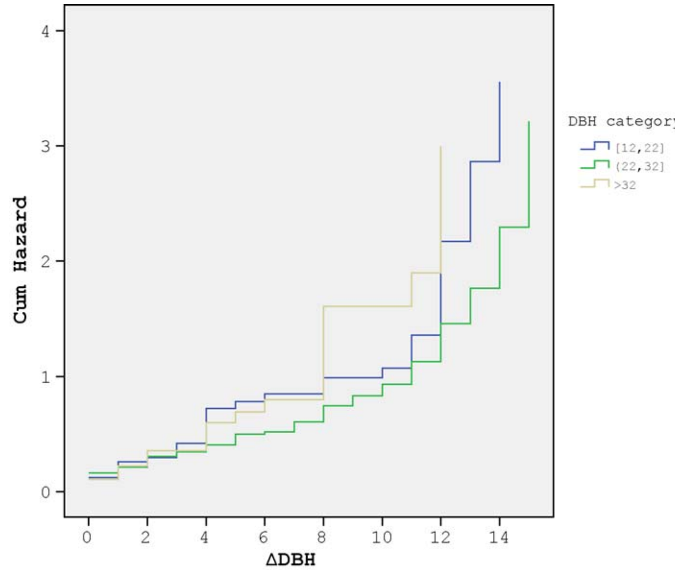


Fig. 2. Hazard functions for time one diameter classes by ΔDBH.

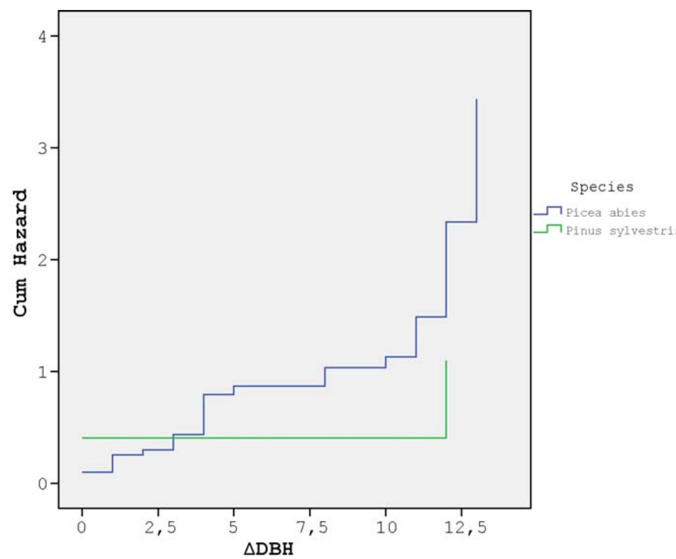


Fig. 3. Hazard functions for time one DBH class [12,22] cm for the two tree species by ΔDBH.

Table 2
Logrank tests for homogeneity of survival distributions by DBH class and CC.

Covariate	χ^2	Degrees of freedom	Τιμή p
DBH class (cm)	4.099	2	0.129
Crown class (CC)	0.915	4	0.922

4. Discussion

A longitudinal unit can be any unit that measures a variable's transition from one state to another [36]. The greatest hurdle in

applying survival analytical techniques to forest inventories is finding appropriate longitudinal units to quantify survival probabilities and mortality hazards [13]. If time or ages are used as longitudinal units in forest inventory analyses, a number of problems may be encountered as evidenced by previous work in forest survival analysis [12,22,23,19]. First, all observations are censored. The exact time of tree death is uncertain with the inventory re-measurement date often serving as the longitudinal measure. Second, the survival function curve is partially dependent on when and where the measurements were taken. For example, if the bulk of mortality is located in a certain area of the state that is inventoried at a discrete point in time, then the resulting survival curve will be biased if time is used. Third, the age of a tree is difficult to estimate in forest inventories. Previous studies in even-aged stand conditions have been able to develop rather flexible survival/hazard functions using individual tree age and time [22,23,19]. However, DBH is a quantity that hypothetically increases with time until a tree dies (Harcombe [12]). Although DBH is not a perfect predictor of tree age, especially in uneven-aged stands, tree diameter could be used as a hypothetical surrogate for age, considering that ΔDBH is zero at time one and tree survey stops at time two, where $\Delta \text{DBH} > 0$. Time (years) may greatly relate to the survivalship of humans, while tree growth over intervals of time (i.e., annual diameter growth) may be a more meaningful metric in forest ecology. Bigler and Bugmann [25] found that using ΔDBH models to refine estimates of time of death greatly improved logistic mortality models. Unfortunately, the longer the inventory re-measurement interval the greater the possibility that ΔDBH may inaccurately reflect time due to the censoring of tree death and variable tree growth rates (particularly in uneven-aged stands).

There are numerous estimation procedures for the survival and hazard functions, each with its own advantages and drawbacks. This study used the elementary life-table Kaplan–Meier estimation procedure as a first attempt to apply survival analysis techniques to a forest inventory; a technique suggested by Harcombe [12] and Woodall et al. [32]. The Kaplan–Meier approach allowed non-parametric estimation of survivorship, the ability to compare survivorship among stratified sample units, and the ability to test association between covariates and survivorship. The survival function quantifies mortality cumulatively through the diameter distribution, while the hazard function may display specific DBH midpoint mortality rates. As suggested by Manion and Griffin [28], the quantification of rates of mortality across diameter classes helps identify atypical mortality trends as soon as they arise. The hazard and survival functions can together provide an initial evaluation of tree mortality and assessment of sustainable development for forest inventories as long as the survey interval of time is approximately the same between re-measurements. Large sampling intervals will affect ΔDBH and ultimately the interpretation or application of syrvival analyses.

Traditionally, insects and disease tree mortality has been expressed in terms of ratios of tree mortality. Hazard functions can be used for more detailed analysis of mortality dynamics for any tree population of interest. He and Alfaro [33] found that survival analysis was useful in analyzing tree resistance to pest attack; however, they also found that tree survival time was related to seasonal temperatures and precipitation. Hazard functions also allow a broad comparison of mortality risk rates among species and diameter classes. For forest inventories, hazard functions may aid investigations between forest mortality and causal agents [12].

With logrank test we can test the hypothesis concerning survival/hazard curves comparison. In this study, the logrank test for effects of covariates on the survival function, time one DBH class and CC, indicated that these covariates were not significant in tree survival. As found in other mortality studies, crown conditions may be an important predictor of individual tree mortality [34]. The ability to associate individual tree traits with mortality hazard has enormous potential benefits for the study of natural processes [13].

5. Conclusion

Forest inventory mortality analyses have predominantly been focused on logistic regression modelling at the individual tree-scale and simple data summarizations. This study proposes an approach to forest mortality evaluation and sustainable development assessment involving combination of established survival modelling techniques (survival/hazard functions) with traditional quantifications of forest stand attributes (DBH distribution and diameter growth). There was an attempt to use DBH and ΔDBH as surrogates for age and time in application of survival analysis. We found that there are no significant differences in survival, between diameter and crown classes, for the Elatia forest. *P. abies* seems to have the greatest risk of mortality (compared to *P. sylvestris*), at small diameter and big diameter growth. This study's approache may eventually lead to more efficient and statistically defensible evaluation of tree mortality and sustainable development assessment for tree populations across different forest types, locations, and suffering from varying damage agents.

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